

Chapter 22

Realizing Interval Type–2 Fuzzy Systems with Type–1 Fuzzy Systems

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ABSTRACT

In this chapter, the authors have realized Interval Type-2 Fuzzy Logic Systems (IT2 FLSs) with the average of two Type-1 Fuzzy Logic Systems (T1 FLSs). The authors have presented two case studies by applying this realization methodology on (i) an arbitrary system, where an IT2 FLS is considered, in which its footprint of uncertainty (FOU) is expressed using Principal T1 FS+FOU approach, and the second (ii) the Mackey-Glass time-series forecasting. In the second case study, T1 FLS is evolved using Particle Swarm Optimization (PSO) algorithm for the Mackey-Glass time-series data with added noise, and is then upgraded to IT2 FLS by adding FOU. Further, four experiments are conducted in this case study for four different noise levels. For each case study, a comparative study of the results of the average of two T1 FLSs and the corresponding IT2 FLS, obtained through computer simulations in MATLAB environment, is presented to demonstrate the effectiveness of the realization approach.

Very low values of Mean Square Error (MSE) and Root Mean Square Error (RMSE) demonstrate that IT2 FLS performance is equivalent to the average of two T1 FLSs. This approach is helpful in the absence of the availability of development tools for T2 FLSs or because of complexity and difficulty in understanding T2 FLSs that makes the implementation difficult. It provides an easy route to the simulation/realization of IT2 FLSs and by following this approach, all existing tools/methodologies for the design, simulation and realization of T1 FLSs can be directly extended to T2 FLSs.

INTRODUCTION

Zadeh in 1965 (Zadeh, 1965) gave the concept of Type-1 Fuzzy Sets (T1 FSs) for modeling uncertainty, vagueness and imprecision. T1 FLSs that use T1 FSs have been successfully used in various domains. However, there are various sources of uncertainties facing T1 FLSs in most of the real world applications. In a broad sense, these uncertainties can be classified in four groups (Mendel and John, 2002):

1. The words that are used in antecedents and consequents of rules can mean different things to different people.
2. Consequents obtained by polling a group of experts will often be different for the same rule because the experts will not necessarily be in agreement.
3. Measurements that activate a T1 FLS may be noisy and therefore uncertain.
4. The data that are used to tune the parameters of a T1 FLS may also be noisy.

T1 FLSs, cannot fully handle these uncertainties because they use precise and crisp T1 FSs. However, T2 FLSs, which use Type-2 FSs (T2 FSs) characterized by fuzzy membership functions (MFs), have an additional third dimension. This third dimension and FOU provide an additional degree of freedom for T2 FLSs to directly model and handle uncertainties (Mendel and John, 2002). Thus, T2 FLSs are expected to perform better than their traditional counter parts. Although T2 FLSs have been used successfully in a number of applications (Hagras, 2004, Liang and Mendel,

2000a, 2001), generally they are difficult to understand and use. T2 FLSs are computationally hard and difficult to visualize and many a times, due to the non availability of suitable software tools, the designer cannot ripe the benefits of T2 FLSs. Whereas, T1 FLSs are much simpler to design, simulate and realize, and their popularity has been greatly aided by the Graphical User Interface (GUI) based software tools like Fuzzy Logic Toolbox (FLT) for MATLAB. The objective of this chapter is to validate that a T2 FLS can be approximated by the average of two T1 FLSs so that all the existing realization methods for T1 FLSs can be directly used for realizing T2 FLSs. Hameed (Hameed, 2009) gave a simplified architecture of a T2 FLS using four embedded T1 FLSs and used it in greenhouse climate control system. In 2010, Castillo *et al.* (Castillo *et al.*, 2010) evolved an IT2 FLS using Human Evolutionary algorithm. They realized their evolved IT2 FLS through average of two T1 FLSs with an objective to show that IT2 fuzzy controllers obtained with the evolutionary algorithm outperform T1 fuzzy controllers.

In this chapter, the realization methodology of approximating an IT2 with the average of two T1 FLSs is applied to two different case studies with a viewpoint to show that the results obtained through this averaging approach are comparable to the results of an IT2 FLS. For quantifying the error, we utilized two widely used performance criteria, these are: value of the mean square error (MSE), and the root mean square error (RMSE). In the first case study, an arbitrary IT2 FLS is considered and in the second case study, an IT2 is obtained by upgrading a genetically evolved T1 FLS. This T1 FLS is evolved from the Mackey-

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